Supplementary Material

A Credible and Robust approach to Ego-Motion Estimation using an Automotive Radar

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This is the supplementary material to the following paper:

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The presented information is not self-contained, instead it should be considered as appendix. For citation, please use the main publication stated above.

In the following, we provide supplementary material to the point-set registration (PSR) example in section 1 for better understanding and visualization. Further, we give additional information for the ANEES evaluation in section 2. Especially, regarding our argument of the ANEES being inconclusive for the summing approach (SA). Finally, section 3 gives a qualitative trajectory evaluation based on our implementations for the robot dataset. Please take into account, that this evaluation should only be considered as benchmark under the mentioned conditions.

1 PSR Example

We evaluated a *Simulated Point Set Registration* example. For a better understanding of the scenario, we reprint an example, already given in [2]. The example in Figure 1 is based on only 10 landmarks with 4 clusters resulting in 18 landmarks.

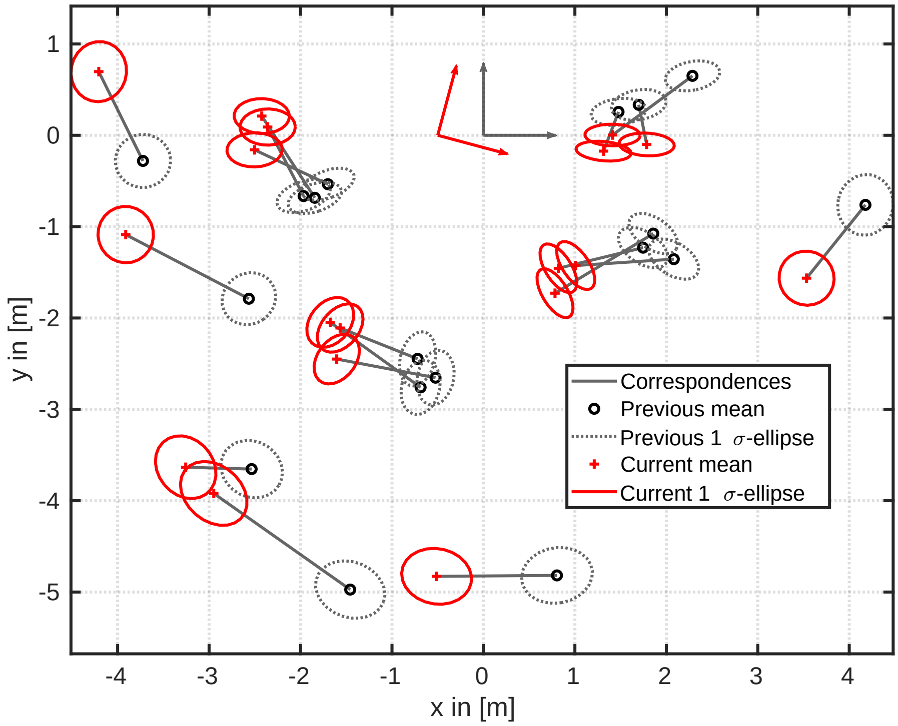

Figure 1: Simplified example for one simulated PSR problem with a ground truth transformation of 0.5 m in x-direction and 15° in rotation. The plot shows the situation after adding a random measurement noise according to [1, Table I]. The visualized correspondence information is unknown to the algorithms.

2 Credibility Analysis

Here, we want to stress the fact, that the ANEES values for the SA in [1, Table II] have to be considered as inconclusive. To underline this, we show the NEES distributions for the clustered point-set registration experiment in comparison with the ideal χ^2-distribution and a fitted χ^2-distribution (based on MLE) in Figure 2 and Figure 3.

As the ANEES is simply the mean of the NEES values, the ANEES would be a vertical line at 3.63 (normalized 1.21) for the MSM and 2.16 (normalized 0.72) for the SA. The normalized ANEES for the SA with 0.72 seems to be close to one and misslead to the conclusion, that the SA is nearly credible, but if we look closer to Figure 3, we see two problems:

- the fitted χ^2-distribution based on the NEES values does not represent the empirical values and
- some SA results are outliers where the optimizer run into wrong local minima resulting in NEES values $\gg 100$ thus, the ANEES shifts into positive direction. Ignoring those outliers, would result in a normalized ANEES of 0.15 for the SA example in Figure 3, which is more representative in this case.

That said, we have to be careful by using the ANEES metric, as stated above. Likewise, experiments based on experimental data may have inaccuracies regarding its ground truth as well as the sensors' noise models. Also, as we use the covariance, the errors should follow a normal distribution, otherwise we would have to define a complex noise model as output of the motion-estimation algorithm.

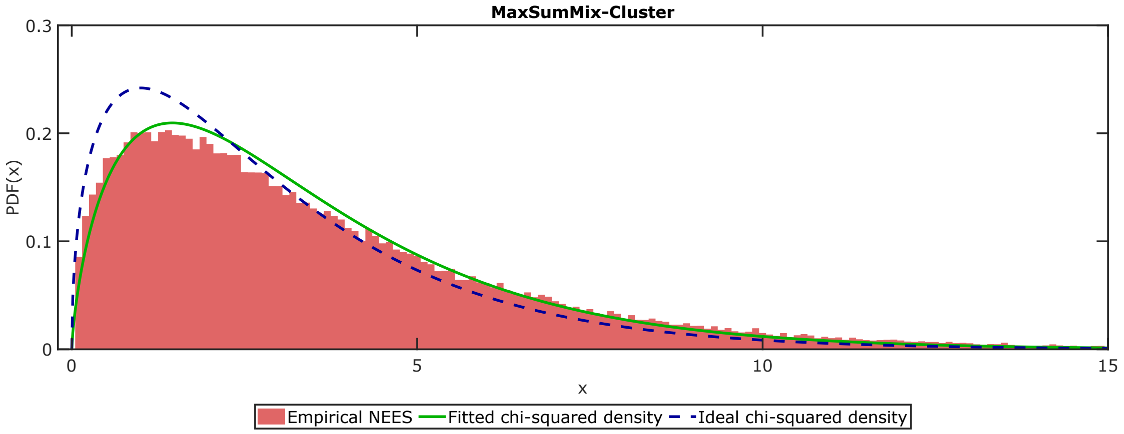

Figure 2: NEES histogram for experiment PSR-C (clustered point-set registration problem), solved with MSM.

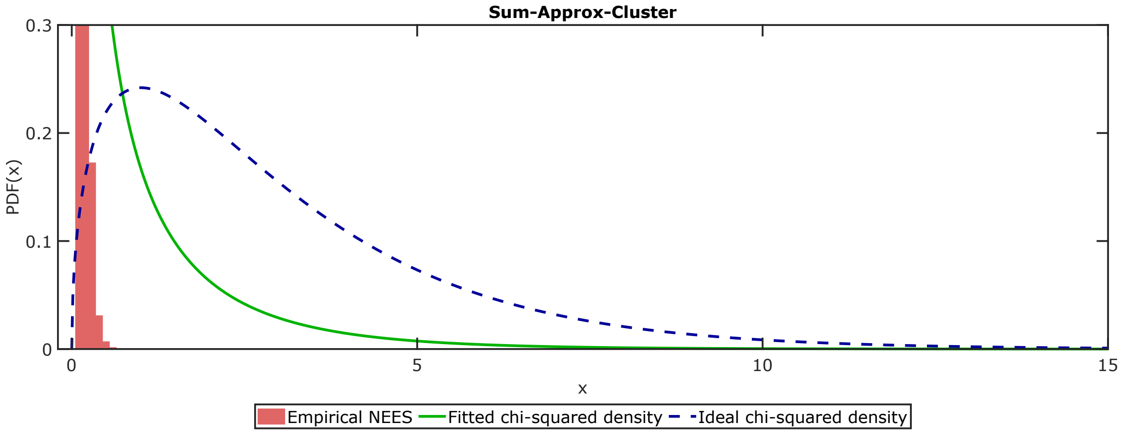

Figure 3: NEES histogram for experiment PSR-C (clustered point-set registration problem), solved with SA.

3 Trajectory Evaluation

We deliberately did not include a qualitative trajectory evaluation within our publication, because we don't want to imply the goal of a stand-alone application of our method. We argue, that our method can be used in a loosely-coupled manner in overlaying algorithms, where it can be thought of as a virtual odometry sensor. For this, the estimator's performance regarding its mean error is not the crucial part, but its credibility.

Using this benchmark for comparison, should be done with care. In our opinion, a direct comparison to other velocity-based methods makes only sense, if:

- they are not already extended by other sensor information
- don't use keyframes or other improvements which makes the algorithm unusable for implementation into overlaying sensor fusion with correct covariance information
- and ideally evaluate the credibility.

For the following trajectory evaluation, we utilized the *rpg trajectory evaluation* tool [3] for our robot dataset[1]. The results are shown in Figure 4 and Figure 5 as well as a qualitative trajectory error in Figure 6. Additionally, Table 1 gives the summarized metrics.

It can be seen, that there is no marginal difference between both approaches (SA and MSM), which is also reflected within the RMSE results for this experiment shown in the accompanied paper [1, Table II]. Especially in the relative translation error, the SA is a bit better, but comes without reliable covariance information, as showed with the ANEES value within [1, Table II]. We conclude, that both algorithms should not be used as a stand-alone variant for motion estimation, but can support a sensor fusion algorithm with their virtual odometry information, if also a *credible covariance* is generated.

Table 1: Results by the *rpg trajectory evaluation* tool for the robot dataset.

	Translation (%)	Rotation ($^\circ\,\mathrm{m}^{-1}$)	Translation RMSE
MSM	75.80	1.49	41.98
SA	64.16	1.56	42.05
MSM-D	75.28	1.43	38.72
SA-D	62.91	1.45	53.04

[1] The nuScenes dataset is omitted on purpose. The scenes are only of 20 s length and differ in its length between zero and $> 100\,\mathrm{m}$, making the trajectory evaluation hard to interpret.

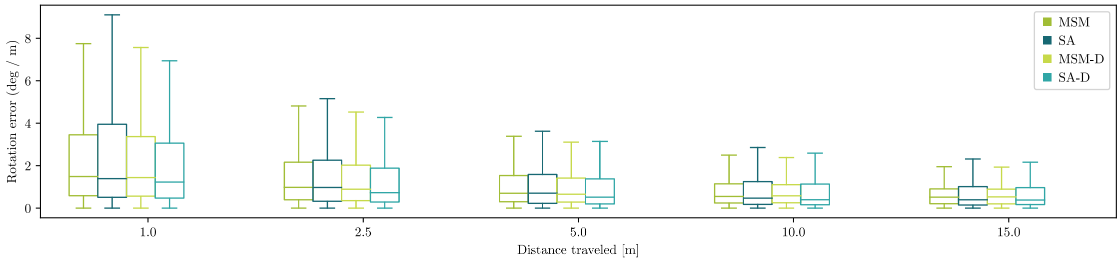

Figure 4: Overall rotation error for the robot dataset, with different subtrajectory length.

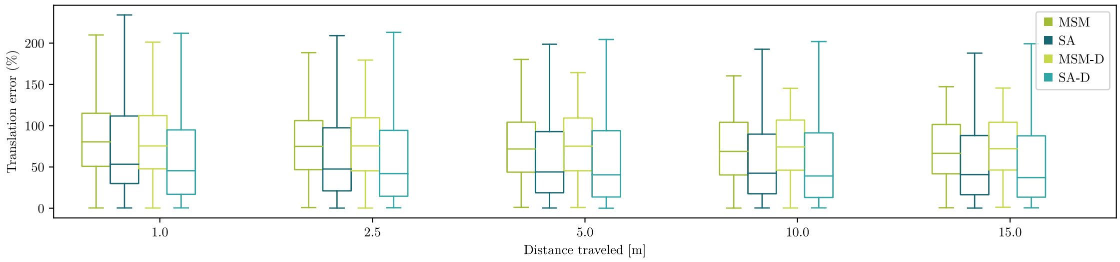

Figure 5: Overall translation error for the robot dataset, with different subtrajectory length.

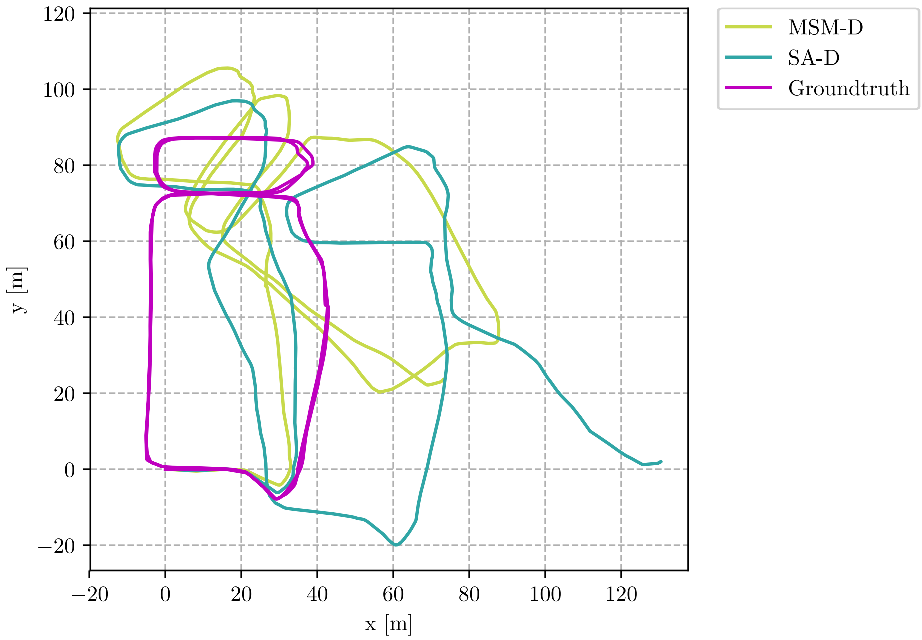

Figure 6: Qualitative trajectory evaluation for the robot dataset.

References

[1] K. Haggag, S. Lange, T. Pfeifer, and P. Protzel, “A Credible and Robust approach to Ego-Motion Estimation using an Automotive Radar,” *IEEE Robotics and Automation Letters*, 2022, submitted.

[2] T. Pfeifer, S. Lange, and P. Protzel, “Advancing Mixture Models for Least Squares Optimization,” *IEEE Robotics and Automation Letters*, 2021, in press.

[3] Z. Zhang and D. Scaramuzza, “A Tutorial on Quantitative Trajectory Evaluation for Visual(-Inertial) Odometry,” in *Proc. of Intl. Conf. on Intelligent Robots and Systems (IROS)*, 2018.